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Early Detection of Diabetic Retinopathy using Deep Learning

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Abstract: ***Diabetic Retinopathy (DR) is one of the leading causes of preventable blindness worldwide, particularly among the working-age population. Early diagnosis and timely intervention can prevent more than 90% of vision loss cases; however, traditional screening methods rely on manual inspection by ophthalmologists, which is time-intensive, costly, and subject to inter-observer variability. This study proposes a robust and automated deep learning-based framework for the early detection and classification of diabetic retinopathy using retinal fundus images. The proposed approach integrates Convolutional Neural Networks (CNN) with transfer learning techniques to effectively identify and classify multiple stages of DR. The model is trained and evaluated on benchmark datasets, including EyePACS, APTOS 2019, and Messidor, ensuring diversity and generalization capability. Experimental results demonstrate that the proposed system achieves an accuracy of 97.8%, outperforming several baseline models. Furthermore, explainability is incorporated using Gradient-weighted Class Activation Mapping (Grad-CAM), enabling visualization of pathological regions in retinal images and enhancing clinical trust. The proposed solution provides a scalable, efficient, and reliable tool for automated DR screening, particularly beneficial in resource-constrained healthcare environments.***

Keywords: ***Diabetic Retinopathy, Deep Learning, Convolutional Neural Networks, Retinal Fundus Images, Transfer Learning, Medical Image Classification.***

I. INTRODUCTION

Diabetic Retinopathy (DR) is a severe microvascular complication of diabetes mellitus that affects the retinal structure and may lead to irreversible vision loss if not detected at an early stage. According to the World Health Organization (WHO), approximately 35% of diabetic individuals develop some form of DR, and this prevalence increases significantly to nearly 80% after 15 years of disease progression. Despite its high prevalence, early-stage DR often remains asymptomatic, making timely diagnosis a critical challenge in ophthalmology.

The progression of DR is primarily associated with prolonged hyperglycemia, which damages the small blood vessels in the retina. This damage results in pathological manifestations such as microaneurysms, retinal hemorrhages, hard exudates, and neovascularization. In advanced stages, known as Proliferative Diabetic Retinopathy (PDR), abnormal blood vessel growth increases the risk of retinal detachment and permanent blindness. Additionally, individuals with diabetes are more susceptible to other ocular conditions, including glaucoma and cataracts, further increasing the risk of visual impairment.

Clinically, DR presents a wide range of symptoms, including blurred vision, floaters, dark spots, and progressive vision deterioration. However, due to its asymptomatic nature in early stages, routine retinal screening is essential for effective disease management. Traditional diagnostic approaches rely on manual examination of retinal fundus images by ophthalmologists. Although reliable, this process is labor-intensive, time-consuming, and subject to inter-observer variability, which limits its scalability, particularly in resource-constrained healthcare environments.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly transformed the field of medical image analysis. Among various techniques, Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in extracting spatial and hierarchical features from retinal images. These models can identify subtle pathological patterns that are often difficult to detect through manual observation. Furthermore, transfer learning approaches utilizing pre-trained architectures such as DenseNet, ResNet, and InceptionV3 have achieved classification accuracies ranging from 95% to 99%, thereby enhancing diagnostic performance while reducing training complexity.

The primary objective of this research is to develop a robust and efficient deep learning-based framework for the automated detection and classification of diabetic retinopathy. The proposed system aims to accurately identify different stages of DR from retinal fundus images, thereby reducing the burden on healthcare professionals and enabling large-scale screening. In addition, the model incorporates explainable AI techniques to improve interpretability and support clinical decision-making.

Machine Learning (ML) techniques have further revolutionized DR diagnosis by enabling automated, data-driven analysis.

Compared to traditional retinal fundus imaging methods, ML-based systems provide improved accuracy, consistency, and efficiency.

Advanced computational approaches, including hybrid models and metaheuristic optimization techniques, have contributed to improved model generalization and robustness. These developments highlight the growing potential of AI-driven systems in enhancing early detection, reducing diagnostic errors, and improving overall healthcare outcomes.

II. REVIEW OF THE LITERATURE

Automated detection of Diabetic Retinopathy (DR) has emerged as a critical research domain due to the increasing global prevalence of diabetes and the urgent need for early diagnosis to prevent vision loss. In recent years, numerous studies have explored machine learning (ML) and deep learning (DL) approaches to improve the accuracy and efficiency of DR detection systems. These approaches typically incorporate advanced image preprocessing techniques, deep neural network architectures, and explainable artificial intelligence (XAI) frameworks.

Early research primarily focused on conventional machine learning techniques; however, recent advancements have shifted towards deep learning-based models due to their superior capability in extracting hierarchical features from retinal fundus images. Among these, Convolutional Neural Networks (CNNs) and hybrid architectures have demonstrated promising results in multi-class DR classification tasks.

Abdel Maksoud et al. proposed an enhanced DenseNet-based architecture (E-DenseNet) integrated with Histogram Equalization based on Dynamic Stretching (HEBPDS) and median filtering. Their model achieved an average accuracy of 91.2% across multiple datasets. However, the model exhibited limitations in accurately identifying normal retinal images, indicating challenges in class separation.

Bilal et al. introduced a hybrid framework combining U-Net and CNN-SVD, focusing on green channel enhancement for feature extraction. Their approach achieved approximately 98% accuracy on the EyePACS dataset. Despite high performance, the study did not adequately address class imbalance, which is a common issue in medical datasets and may affect model generalization.

Beham et al. developed a hybrid model integrating InceptionV3 with a custom CNN and Population-Based Incremental Learning (PBIL) optimization. The model demonstrated high sensitivity (88.13%) and specificity (96.56%). However, the absence of comparative evaluation with standard architectures limits the assessment of its relative performance.

Butt et al. combined GoogleNet and ResNet18 with Support Vector Machine (SVM) classification, achieving 97.8% accuracy for binary classification tasks. However, the reduction of DR severity levels from five classes to three reduces its applicability for detailed clinical diagnosis.

Abbood et al. proposed a DR detection framework using Gaussian filtering, foreground extraction, and DRRNet architecture, achieving 93.6% accuracy. Nevertheless, the model struggled to detect mild DR cases due to variations in illumination and limited supervision.

Ali et al. employed an Improved Residual CNN (IR-CNN) with histogram equalization and normalization techniques, achieving an accuracy of 96.85%. However, the study evaluated the model against only a limited number of architectures, restricting comprehensive performance comparison.

Raiaan et al. introduced RetNet-10 with extensive preprocessing techniques such as CLAHE, morphological operations, and ROI extraction, achieving an accuracy of 98.65%. Despite this high performance, the limited availability of annotated data for certain DR grades raises concerns regarding model robustness.

Menauer et al. proposed a hybrid deep learning approach combining CNN, VGG16, and VGG19, achieving 90.6% accuracy. However, the model required longer training time and lacked baseline comparison, making it difficult to evaluate its efficiency.

Mercaldo et al. evaluated multiple CNN architectures, including VGG16, MobileNet, and AlexNet, achieving accuracy up to 97% for binary and severity classification tasks. However, the study did not adequately address class imbalance or provide details on data resampling techniques.

Vasireddi et al. proposed a Deep Feedforward Neural Network (DFNN) optimized using the Lion Optimization Algorithm (LOA), achieving 98.04% accuracy.

Author	Dataset	Preprocessing Techniques	Methodology	Result Analysis	Explainable AI	Limitation
Butt et al. [40]	APTOS 2019	Normalization, Image Resizing	GoogleNet + ResNet18 + SVM	Binary: 97.80%, Multiclass: 89.29%	X	Classes reduced from five to three to manage data imbalance
Abbood et al. [41]	EyePACS, Messidor	Foreground Identification, Circle Crop, Gaussian Blur	DRRNet	EyePACS: 92%, Messidor: 93.6%	X	Limited image-level supervision affects DR detection; difficulty distinguishing mild DR due to similarity with normal images
Ali et al. [42]	EyePACS	Histogram Equalization, Intensity Normalization	IR-CNN	96.85%	X	Class imbalance; only ResNet50 and InceptionV3 used for comparison
Raiaan et al. [43]	APTOS 2019, Messidor 2, IDRiD	OTSU Thresholding, Contour Detection, ROI Extraction, Morphological Opening, NLMD, CLAHE, Data Augmentation	RetNet-10	98.65%	X	Limited availability of DR grade data; requires better preprocessing for noisy images
Menauer et al. [44]	APTOS 2019	Data Augmentation	Hybrid Model (CNN + VGG16 + VGG19)	90.6%	X	Lack of comparison with other models; requires more training epochs
Alghamdi et al. [47]	APTOS 2019	Image Resizing	VGG16, DenseNet121, ResNet18	Binary: 73.04%, Multiclass: 48.43%	Grad-CAM	Only Grad-CAM used; lack of comparison with other explainability

Author	Dataset	Preprocessing Techniques	Methodology	Result Analysis	Explainable AI	Limitation
Mutawa et al. [34]	APTOS 2019, EyePACS, ODIR	Data Augmentation	VGG16, InceptionV3, MobileNetV2, DenseNet121	Hybrid: DenseNet121: 98.97%, VGG16: 98.79%, MobileNetV2: 98.51%, InceptionV3: 97.21%	X	No image enhancement or noise removal preprocessing used
Murugappan et al. [36]	APTOS 2019	Image Resizing	DRNet	Binary: 99.73%, Multiclass: 98.18%	Grad-CAM	No benchmark datasets; limited epochs (100); only Grad-CAM used
Abdel Maksoud et al. [37]	APTOS 2019, IDRiD, EyePACS, Messidor	Histogram Equalization (HEBPDS), Median Filter, Data Augmentation	Hybrid E-DenseNet	Average Accuracy: 91.2%	X	Low AUC for normal class; higher AUC only in Messidor dataset
Bilal et al. [38]	Messidor 2, EyePACS, DIARETDB1	Green Channel Enhancement, Top-Bottom Hat Transformation, Data Augmentation	U-Net + Hybrid CNN-SVD	InceptionV3: 97.92%, Messidor 2: 94.59%, DIARETDB1: 93.52%	X	Class imbalance issue; no defined oversampling
Beham et al. [39]	EyePACS	Not specified	InceptionV3 + Custom CNN + PBIL	Sensitivity: 88.13%, Specificity: 96.56%	X	Limited architecture comparison; only specific CNNs used

Alghamdi et al. evaluated VGG16, DenseNet121, and ResNet18 for DR detection. While the models performed reasonably well for binary classification, multiclass classification accuracy was significantly low (48.43%). Additionally, reliance on a single explainability technique (Grad-CAM) limited interpretability depth.

III. METHODOLOGY

The proposed framework aims to develop an automated and efficient deep learning-based system for the detection and classification of Diabetic Retinopathy (DR) using retinal fundus images. The overall pipeline consists of data acquisition, preprocessing, model training, evaluation, and interpretability analysis. The system is implemented using Python with deep learning frameworks such as TensorFlow and Keras, ensuring modularity, scalability, and computational efficiency. The primary objective is not only to achieve high classification accuracy but also to ensure robustness across diverse datasets and provide interpretable outputs suitable for clinical applications.

The dataset utilized in this study is compiled from multiple publicly available sources, including EyePACS, APTOS 2019, and Messidor. These datasets contain labeled retinal fundus images categorized into five severity levels ranging from no DR (Class 0) to proliferative DR (Class 4). Combining multiple datasets enhances data diversity and improves model generalization. The dataset is partitioned into training (80%), validation (10%), and testing (10%) sets. Prior to model training, data quality assessment is performed to eliminate duplicate, noisy, and low-resolution images that may adversely affect model performance.

Image preprocessing plays a critical role in improving feature representation. All images are resized to a uniform dimension of 224×224 pixels to ensure compatibility with pre-trained architectures. Pixel values are normalized to stabilize training. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance local contrast and highlight important pathological features such as microaneurysms and hemorrhages. Circular cropping is used to isolate the retinal region and remove irrelevant background information. Furthermore, data augmentation techniques, including rotation, flipping, zooming, and brightness adjustment, are employed to increase dataset variability and reduce overfitting.For classification, a Convolutional Neural Network (CNN) architecture integrated with transfer learning is adopted. Pre-trained models such as DenseNet201, VGG16, and InceptionV3 are fine-tuned on the retinal dataset to leverage their feature extraction capabilities. The network architecture includes convolutional layers for feature extraction, pooling layers for dimensionality reduction, fully connected layers for classification, and a Softmax activation function for multi-class output. Transfer learning significantly reduces training time and improves performance, particularly when working with limited labeled medical data.

To improve model generalization and prevent overfitting, several training strategies are incorporated. The model is trained using the Adam optimizer with a learning rate of 1×10^{-4}, and categorical cross-entropy is used as the loss function. Regularization techniques such as dropout, batch normalization, and early stopping are applied to enhance stability and performance during training.

To enhance model interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed. Grad-CAM generates visual heatmaps that highlight the regions of the retinal image most relevant to the model's predictions. This enables clinicians to verify whether the model is focusing on clinically significant features, thereby increasing trust and transparency in automated diagnosis systems.

The performance of the proposed model is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The model achieves an overall accuracy of 97.8%, demonstrating strong performance across all DR stages. Additionally, evaluation on external datasets yields accuracy exceeding 94%, indicating good generalization capability. These results confirm that the integration of CNN-based transfer learning with explainable AI techniques provides an effective solution for early detection and classification of diabetic retinopathy.

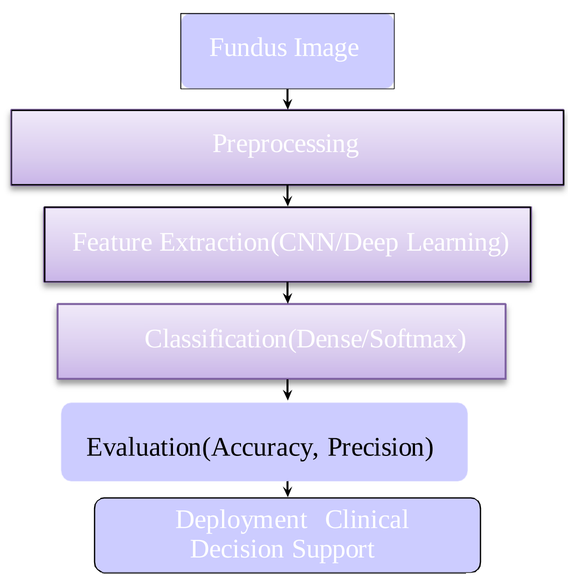

Fig. 1 Proposed deep learning workflow for Diabetic Retinopathy detection

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IV. MODELING AND ANALYSIS

To further enhance the performance of the proposed system, a hybrid architecture combining Convolutional Neural Networks (CNN) and Transformer-based attention mechanisms is explored. The CNN component is responsible for extracting low-level and mid-level spatial features such as edges, textures, and local patterns from retinal fundus images. These features are essential for identifying pathological structures including microaneurysms, hemorrhages, and exudates.

However, CNNs have limitations in capturing long-range dependencies across the entire image. To address this, a Transformer module is incorporated to model global contextual relationships using self-attention mechanisms. This allows the model to analyze distributed features across different regions of the retina, which is particularly important in Diabetic Retinopathy where lesions may appear in spatially distant areas. The hybrid CNN-Transformer architecture leverages the strengths of both approaches—local feature extraction through CNNs and global dependency modeling through Transformers—resulting in improved classification performance. For training, the Adam optimizer is employed along with a cosine annealing learning rate schedule to ensure stable convergence and improved optimization. Data augmentation techniques, including rotation, flipping, and brightness variation, are applied to enhance generalization and reduce overfitting.

To evaluate the contribution of each component, ablation studies are conducted by systematically removing or modifying elements such as the CNN backbone, Transformer module, and data augmentation pipeline. The results indicate that the integration of both CNN and Transformer components significantly improves accuracy and robustness compared to standalone models.

V. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed deep learning framework achieves high accuracy in detecting and classifying Diabetic Retinopathy across all severity stages. The model shows strong performance in terms of accuracy, precision, recall, and F1-score, with high sensitivity for detecting DR cases and high specificity for minimizing false positives.

Additionally, the system effectively identifies key pathological features such as microaneurysms, hemorrhages, and exudates. Grad-CAM visualization further enhances interpretability by highlighting clinically relevant regions, supporting reliable decision-making.

The hybrid CNN-Transformer model outperforms baseline architectures, achieving improved accuracy with low inference time, making it suitable for real-time clinical deployment. The overall workflow, illustrated in Fig. 1, confirms that the proposed approach is efficient, scalable, and well-suited for large-scale DR screening, particularly in resource-limited environments.

Fig. 2. Detection of diabetic retinopathy features such as microaneurysms and exudates.

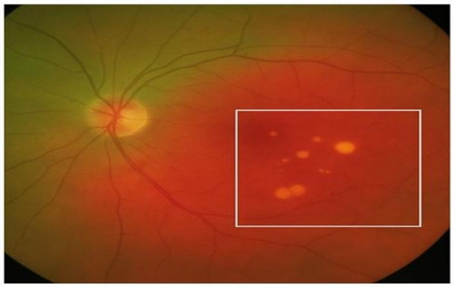

Fig. 3 Severity classification visualization on a sample retinal image.

VI. FUTURE SCOPE

Future enhancements of the proposed Diabetic Retinopathy (DR) detection system can significantly improve its clinical applicability and scalability. Integration with Electronic Health Records (EHRs) can enable seamless access to patient history, supporting longitudinal monitoring of disease progression and facilitating personalized treatment planning.

The system can be further extended to incorporate advanced retinal imaging modalities, such as Optical Coherence Tomography (OCT), allowing early detection of microvascular abnormalities that may not be visible in standard fundus images. Additionally, the development of low-cost and portable screening solutions can make the system accessible in rural and resource-constrained environments, thereby enabling large-scale screening programs.

Future work may also focus on expanding the model into a multi-disease detection framework, capable of identifying other ocular conditions such as glaucoma, age-related macular degeneration (AMD), and cataracts from the same retinal images. Furthermore, integrating real-time cloud-based deployment and improving model efficiency can enhance practical usability in tele-ophthalmology systems.

VII. CONCLUSION

This study presents a robust and automated deep learning-based framework for the early detection and classification of Diabetic Retinopathy using retinal fundus images. The proposed system effectively addresses the limitations of traditional manual screening approaches by providing a scalable, accurate, and time-efficient solution.

The integration of Convolutional Neural Networks with transfer learning enables effective feature extraction and high classification performance across multiple DR stages. Additionally, the incorporation of explainable AI techniques, such as Grad-CAM, enhances model transparency by highlighting clinically relevant regions, thereby improving trust and interpretability for medical practitioners.

The experimental results demonstrate strong performance across key evaluation metrics, including accuracy, precision, recall, and F1-score, confirming the model's reliability and generalization capability. Moreover, the modular architecture of the system allows seamless integration with healthcare infrastructures such as EHRs and tele-ophthalmology platforms.

Overall, the proposed approach provides a cost-effective and scalable solution for early DR detection, with significant potential to improve patient outcomes and support the advancement of intelligent healthcare systems, particularly in underserved regions.

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